

Recall: A set of vectors $S = \{\vec{x}_1, \dots, \vec{x}_k\} \in \mathbb{R}^n$

is orthogonal if 1) $\vec{x}_i \neq \vec{0}_n$ for all i .

2) $\langle \vec{x}_i, \vec{x}_j \rangle = 0$
for $i \neq j$.

geometrically, this
corresponds to being
at right angles:



Recall: Theorem: let $S = \{\vec{x}_1, \dots, \vec{x}_k\}$ be orthog.

let $\vec{v} = \sum_{i=1}^k \alpha_i \vec{x}_i$, $\vec{w} = \sum_{j=1}^k \beta_j \vec{x}_j$.

Then $\langle \vec{v}, \vec{w} \rangle = \sum_{i=1}^k \alpha_i \beta_i \langle \vec{x}_i, \vec{x}_i \rangle$.

This theorem tells us that it is often useful to express vectors as linear combinations of orthogonal vectors.

Theorem: Suppose $\vec{v} \in \mathbb{R}^n$, $\{\vec{x}_1, \dots, \vec{x}_k\}$ orthogonal,
& $\vec{v} = \sum_{i=1}^k \alpha_i \vec{x}_i$.

Then
$$\alpha_i = \frac{\langle \vec{x}_i, \vec{v} \rangle}{\langle \vec{x}_i, \vec{x}_i \rangle}.$$

Remark: this theorem allows us to quickly compute α_i (much faster than using row reduction).

Proof:
$$\langle \vec{x}_i, \vec{v} \rangle = \langle \vec{x}_i, \sum_{j=1}^k \alpha_j \vec{x}_j \rangle$$

$$= \sum_{j=1}^k \langle \vec{x}_i, \alpha_j \vec{x}_j \rangle \quad (\text{distribute})$$

$$= \sum_{j=1}^k \alpha_j \langle \vec{x}_i, \vec{x}_j \rangle$$

$$= \alpha_i \langle \vec{x}_i, \vec{x}_i \rangle \quad (\text{since } \langle \vec{x}_i, \vec{x}_j \rangle = 0 \text{ for } i \neq j)$$

Hence $\frac{\langle \vec{x}_i, \vec{v} \rangle}{\langle \vec{x}_i, \vec{x}_i \rangle} = \alpha_i \quad \square$

Example: let $\vec{x}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\vec{x}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$

Claim: \vec{x}_1, \vec{x}_2 are orthogonal.

$$\langle \vec{x}_1, \vec{x}_2 \rangle = 1 \cdot 1 + 1(-1) = 0.$$

\square

$$\text{let } \vec{v} = 3\vec{x}_1 + 2\vec{x}_2 = \begin{bmatrix} 5 \\ 1 \end{bmatrix}.$$

Let's check that our theorem gives the correct answers in this case:

$$\alpha_1 = \frac{\langle \vec{x}_1, \vec{v} \rangle}{\langle \vec{x}_1, \vec{x}_1 \rangle} = \frac{(1 \cdot 5 + 1 \cdot 1)}{(1 \cdot 1 + 1 \cdot 1)} = \frac{6}{2} = 3.$$

$$\alpha_2 = \frac{\langle \vec{x}_2, \vec{v} \rangle}{\langle \vec{x}_2, \vec{x}_2 \rangle} = \frac{(1 \cdot 5 + (-1) \cdot 1)}{(1 \cdot 1 + (-1)(-1))} = \frac{4}{2} = 2.$$

Orthogonal bases

Definition: An orthogonal basis of a subspace

$V \subset \mathbb{R}^n$ is a basis of V which

\dots

is also orthogonal.

Recall: a basis $S = \{\vec{x}_1, \dots, \vec{x}_n\}$ of V is a set of vectors such that:

1) S is linearly independent

2) $\langle S \rangle = V$.

Example: let $V = \mathbb{R}^3$.

$$1) \vec{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \vec{x}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \vec{x}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Exercise: check that this is an orthogonal basis.

$$2) \vec{x}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \vec{x}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad \vec{x}_3 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \vdots \\ 1 \end{bmatrix} \quad \dots \quad \begin{bmatrix} 1 \\ \vdots \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Exercise: check that this is an orthogonal basis.

Theorem: Let $\vec{x}_1, \dots, \vec{x}_k$ be orthogonal. Then $\vec{x}_1, \dots, \vec{x}_k$ are linearly independent.

Proof: Suppose $\alpha_1 \vec{x}_1 + \dots + \alpha_k \vec{x}_k = \vec{0}_n$.

Want to show that $\alpha_1, \dots, \alpha_k = 0$.

$$\alpha_i = \frac{\langle \vec{x}_i, \sum_{j=1}^k \alpha_j \vec{x}_j \rangle}{\langle \vec{x}_i, \vec{x}_i \rangle}$$

by our previous theorem

$$= \frac{\langle \vec{x}_i, \vec{0}_n \rangle}{\langle \vec{x}_i, \vec{x}_i \rangle} = \frac{0}{\langle \vec{x}_i, \vec{x}_i \rangle} = 0. \quad \checkmark.$$

In our formulas, the expression $\langle \vec{x}_i, \vec{x}_i \rangle$ keeps popping up. To simplify things, we make the following def:

Definition: $\{\vec{x}_1, \dots, \vec{x}_k\} \subset \mathbb{R}^n$ is called orthonormal

if 1) $\{\vec{x}_1, \dots, \vec{x}_k\}$ is orthogonal

2) $\langle \vec{x}_i, \vec{x}_i \rangle = 1.$



orthogonal



orthonormal

orthogonal

orthonormal

Remark: very similar to orthogonality, but simplifies lots of formulas.

Theorem: Let $V \subset \mathbb{R}^n$ be a subspace.

Then V has an orthonormal basis.

To prove this theorem, one can write down an algorithm that produces such a basis:

The Gram-Schmidt algorithm:

Start with a basis of V , b_1, \dots, b_k .

We will modify $\vec{b}_1, \dots, \vec{b}_k$ to produce an orthonormal basis of V , $\vec{x}_1, \dots, \vec{x}_k$.

$$1) \quad \vec{x}_1 = \frac{\vec{b}_1}{|\vec{b}_1|}$$

$$2a) \quad \vec{x}_2' = \vec{b}_2 - \langle \vec{b}_2, \vec{x}_1 \rangle \vec{x}_1$$

$$2b) \quad \vec{x}_2 = \frac{\vec{x}_2'}{|\vec{x}_2'|}$$

$$3a) \quad \vec{x}_3' = \vec{b}_3 - \langle \vec{b}_3, \vec{x}_1 \rangle \vec{x}_1 - \langle \vec{b}_3, \vec{x}_2 \rangle \vec{x}_2$$

$$3b) \quad \vec{x}_3 = \frac{\vec{x}_3'}{|\vec{x}_3'|}$$

$$\begin{aligned} & \vdots \\ j^a) \quad \vec{x}_j' &= \vec{b}_j - \sum_{i < j} \langle \vec{b}_j, \vec{x}_i \rangle \vec{x}_i \\ j^b) \quad \vec{x}_j &= \frac{\vec{x}_j'}{\|\vec{x}_j'\|} \end{aligned}$$

We thus obtain k new vectors $\vec{x}_1, \dots, \vec{x}_k$.

Theorem: $\vec{x}_1, \dots, \vec{x}_k$ is an orthonormal basis of V .

Proof: 1) We check $\langle \vec{x}_i, \vec{x}_j \rangle = 0$ for $i \neq j$.

Since $\langle \vec{x}_i, \vec{x}_j \rangle = \langle \vec{x}_j, \vec{x}_i \rangle$, we can

assume $i < j$. We proceed by induction

on j . Hence, suppose $\langle \vec{x}_i, \vec{x}_\ell \rangle = 0$ for

$\ell < j$, $\ell \neq i$. Then:

$$\langle \vec{x}_i, \vec{x}_j \rangle = \langle \vec{x}_i, \frac{\vec{x}_j'}{|\vec{x}_j'|} \rangle = \frac{1}{|\vec{x}_j'|} \langle \vec{x}_i, \vec{x}_j' \rangle$$

$$= \frac{1}{|\vec{x}_j'|} \langle \vec{x}_i, \vec{b}_j - \sum_{\ell < j} \langle \vec{b}_j, \vec{x}_\ell \rangle \vec{x}_\ell \rangle$$

$$= \frac{1}{|\vec{x}_j'|} (\langle \vec{x}_i, \vec{b}_j \rangle - \langle \vec{b}_j, \vec{x}_i \rangle) = 0.$$

use
inductive
hypothesis:

Exercise: express \vec{b}_j as a linear combination of the \vec{x}_i . Conclude that

$$\langle \vec{x}_1, \dots, \vec{x}_k \rangle = \langle \vec{b}_1, \dots, \vec{b}_k \rangle.$$

Exercise: Conclude that $\vec{x}_1, \dots, \vec{x}_k$ is an orthonormal basis of V_0 .

Example: $V = \mathbb{R}^3$ $\vec{b}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$ $\vec{b}_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$ $\vec{b}_3 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$

Apply GS to $\vec{b}_1, \vec{b}_2, \vec{b}_3$:

$$\vec{x}_1 = \frac{\vec{b}_1}{\|\vec{b}_1\|} = \frac{\vec{b}_1}{\sqrt{1 \cdot 1 + 1 \cdot 1 + 0 \cdot 0}} = \frac{\vec{b}_1}{\sqrt{2}} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix}.$$

$$\vec{x}_2 = \vec{b}_2 - \langle \vec{b}_2, \vec{x}_1 \rangle \vec{x}_1$$

$$= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \left(1 \cdot \frac{1}{\sqrt{2}} + 1 \cdot \frac{1}{\sqrt{2}} + 1 \cdot 0 \right) \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - (2) \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\vec{x}_2 = \frac{\vec{x}_2^0}{\|\vec{x}_2^0\|} = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}$$

$$\begin{aligned} \vec{x}_3^0 &= \vec{b}_3 - \langle \vec{b}_3, \vec{x}_1^0 \rangle \vec{x}_1^0 - \langle \vec{b}_3, \vec{x}_2^0 \rangle \vec{x}_2^0 \\ &= \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} - \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} - 0 \cdot \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ 0 \end{bmatrix} \end{aligned}$$

$$\vec{x}_3 = \frac{\vec{x}_3^0}{\|\vec{x}_3^0\|} = \frac{\vec{x}_3^0}{\sqrt{(\frac{1}{2})^2 + (\frac{1}{2})^2}} = \frac{\vec{x}_3^0}{\sqrt{\frac{1}{2}}} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix}$$

0 1 1 1 1 1 1 1

Remark: To prove that the GJ algorithm

really does produce a basis, need only
check that each \vec{b}_i is a lin. combination
of $\vec{x}_1, \dots, \vec{x}_k$.